Adoption of Drought Tolerant Maize Varieties under Rainfall Stress in Malawi

Samson P. Katengeza*[1], Stein T. Holden[1] and Rodney W. Lunduka[2]

Paper prepared for presentation at the Fifth Conference of the African Association of Agricultural Economists (5th CAAAE), 23-26 September 2016, Addis Ababa, Ethiopia

[1] Norwegian University of Life Sciences, School of Economics and Business, P.O. Box 631, 1432 Ås, Norway
[2] CIMMYT- Southern Africa Regional Office (SARO), PO Box MP 163, Mount Pleasant Harare, Zimbabwe
* Corresponding author, samkatengeza@gmail.com, Phone: +265 888 705 351, +47 486 433 426

Adoption of Drought Tolerant Maize Varieties under Rainfall Stress in Malawi

Abstract

This paper examines adoption of drought tolerant maize varieties under rainfall stress in Malawi using correlated random effects Probit and Tobit models with control function approach. Drought tolerant maize is a promising technology that has the capacity to help smallholder farmers adapt to drought risks. Using 2009, 2012 and 2015 data from six districts, results show adoption has increased from 46% in 2009 to 59% in 2015. The likelihood of adoption is significantly increased by drought with early droughts having greater impact (31%) than late droughts (20%). Early droughts are also associated with an increased acreage of land allocated to drought tolerant maize and quantity of seed planted. However lagged drought variables appear to negatively affect adoption. The possible explanation is that the years preceding the surveys were associated with good rains such that farmers responded by buying less of drought tolerant maize anticipating similar rainfall pattern. Another important driver of adoption is the farm input subsidy programme. However, while access to subsidised seed increases both adoption and intensity of adoption, previous year's access has a negative impact. This suggests that the increased adoption is due to availability of cheap seed as opposed to farmers' previous exposure to the varieties. This may indicate limited awareness on the benefits of drought tolerant maize varieties. This is also consistent with extension visits positively affecting adoption. Good extension messages and promotion of drought tolerant maize varieties should be improved to allow farmers make informed decisions.

Key words: Drought tolerant maize, drought exposure, farm input subsidy programme, correlated random effects, Malawi

Introduction

Recurrent extreme weather events such as droughts and floods undermine crop yields and aggregate production thereby reducing food availability and agricultural incomes especially among smallholder farmers in developing countries (Davies et al., 2009; Kassie et al., 2009; Kato et al., 2011; Pauw et al., 2011). Failure by farm households to adapt to such weather shocks worsens negative effects of these extreme weather events and inhibits further investment and economic growth both by households and national level (Kassie et al., 2014; Kassie et al., 2009; Kato et al., 2011; Nangoma, 2007). The extreme weather events kick start a knock-on effect that start from low production to food insecurity and local and national economic shock (Devereux, 2007). Malawi is one of many countries in developing world greatly affected by negative impacts of weather extremes. In past two decades, the country has experienced several adverse climatic hazards that have led to severe crop losses, infrastructure damages and occasional displacement of people (Nangoma, 2007; Pangapanga et al., 2012; Pauw et al., 2010). The most recent shocks include droughts of 2004/05 and 2011/12 (Holden & Fischer, 2015; Holden & Mangisoni, 2013) and 2014/15 flash floods early in the growing season and droughts thereafter.

Investing in agricultural production methods that boost farmers' resilience against weather shocks through climate change adaptation and disaster risk reduction approaches is a key strategy to reduce negative impacts (Davies et al., 2009; Pangapanga et al., 2012). In a country with poor or missing markets for insurance and credit and little off-farm activities, adoption of agricultural management strategies that reduce production risks is the only realistic option for smallholder farmers (Kassie et al., 2014). Drought tolerant (DT) maize variety is one potential technology that has the capacity to help smallholder farmers adapt to drought risks. It is estimated that DT maize can produce up to 30% of their potential yield after six weeks of water stress, before and during flowering and grain-formation (Magorokosho et al., 2009; Mangisoni et al., 2011). In Malawi maize is life such that the absence of the commodity is synonymous to food insecurity (Katengeza *et al.*, 2012). Production is predominantly rain fed and prone to frequent droughts which may result in 50% yield loss (Fisher *et al.*, 2015).

The government of Malawi has consequently taken a leading role in promoting and disseminating DT maize varieties through the farm input subsidy programme (FISP) and the

Agricultural Sector Wide Approach programme (ASWAp). Through the ASWAp, the government's long-term objective is to promote sustainable and climate-smart agriculture development (Asfaw et al., 2014) and shift from drought and flood prone farming systems to methods that improve farmers' adaptive capacity, enhance resilience and resource use efficiency, increase crop yield and reduce yield variability in the face of weather extremes (Garrity et al., 2010; Lipper et al., 2014). FISP has consequently been reported as a major determinant of DT maize adoption in Malawi (Holden & Fisher, 2015). Fisher *et al.* (2015) cited unavailability of seed and high seed price as barriers to adoption of DT maize emphasising the importance of farm input subsidy program in enhancing accessing to DT maize seed.

Adoption of DT maize varieties has been previously studied (Fisher et al, 2015: Holden and Fisher, 2015). Fisher et al. (2015) used cross sectional data from six countries in Africa where Drought Tolerant Maize for Africa (DTMA) project is promoting dissemination of drought tolerant maize varieties including Malawi while Holden and Fisher (2015) used three year panel data (2006, 2009 and 2012) for Malawi. These studies looked at general adoption of the DT maize varieties. We build on these two studies using three year panel data (2009, 2012 and 2015) for Malawi to examine adoption of DT maize varieties under rainfall stress conditions. We believe that exposure to drought condition and knowledge of the benefits of the DT maize varieties may trigger a change in farmers' behaviour to adopt to the new varieties. Our data covers three important weather variations namely normal rainfall in 2009, early droughts in 2012 and a combination of flash and riverine floods and late droughts in 2014/15. The paper addresses the following hypotheses: (1) Exposure to drought increases farmers' likelihood of adopting drought tolerant maize varieties; (2) access to farm input subsidy program increases adoption of drought tolerant maize varieties; (3) past exposure to drought tolerant maize varieties increases adoption in the following years.

Model Specification and Estimation Strategy

Adoption methods

Farmers' adoption decision of DT maize is modelled as in Holden and Fisher (2015) based on three year panel data (2009, 2012 and 2015). The model is specified as follows:

$$DT_{ipt} = \alpha_0 + \alpha_1 R_{dt} + \alpha_2 Dr_{it} + \alpha_3 S_{ipt} + \alpha_4 H_{it} + \alpha_5 P_{ipt} + \alpha_6 Ds_{it} + \alpha_i + \varepsilon_{ipt} \qquad 1$$

where DT_{ipt} is the dependent variable and is a dummy on whether household *i* grew DT maize on plot *p* in year *t* or not. The explanatory variables captured as X_{ipt} are defined as follows: R_{dt} is a vector of variables capturing rainfall stress (times of dry spells, times of early and late dry spells) in the farmer' district *d* in year *t*. Dr_{it} is farmer *i* perception on exposure to drought in year *t*. S_{ipt} is a vector of institutional variables such as a dummy for access to subsidized inputs and used them on the plot, visits by extension workers and whether farm household accessed input credit. H_{it} denotes household characteristics. P_{ipt} controls for observable farm plot characteristics such as soil type, slope, fertility status, plot size and distance to plot from home while Ds_{it} controls for location variables (survey districts). α_i captures unobservable time-invariant characteristics of households and farms such as managerial ability and unobservable land quality. ε_{ipt} is normally distributed error term and we assume is independent of X_{ipt}.

Parameters in equation (1) can be estimated by either fixed effects (FE) Probit or correlated random effects (RE) Probit. The FE method removes the unobserved effect (α_i) by time demeaning the data. The fixed effects Probit thus sweeps away all explanatory variables that are constant over time (Wooldridge, 2014). Again fixed effects estimation may cause incidental parameters problem especially when unobserved effects (α_i) are taken as parameters to be estimated (Wooldridge, 2009). The alternative method is the random effects estimator. The traditional RE Probit model assumes that unobserved effects (α_i) and explanatory variables (X_i) are independent, i.e.

$$Cov(X_{it}, \alpha_{it}) = 0, t = 1, 2, \dots, T, \& \; i = 1, \dots, n \qquad 2$$

and that α_i is normally distributed, i.e.:

$$\alpha_i | X_i \sim N(0, \sigma_\alpha^2) \qquad 3$$

The validity of this unconditional normality depends on some restrictive assumptions but becomes more reasonable as T gets large (Wooldridge, 2009). Thus, Arslan *et al.* (2014) proposes testing the unconditional normality within conditional maximum likelihood (CMLE) framework. The CMLE approach allows α_i and X_i to be correlated (Chamberlain, 1980; Wooldridge, 2010) assuming that

$$\alpha_i|X_i \sim N(\varphi + \delta\bar{X}_i, \sigma_\gamma^2) \qquad 4$$

where σ_α^2 is the variance of $\alpha_i$in the equation $\alpha_i = |(\varphi + \delta\overline{X_\imath} + \gamma_i)$

and $\bar{X}_i \equiv T^{-1}\sum_{t=1}^{T} X_{it}$ is the 1 × K vector of time averages.

This approach enables the paper to estimate partial effects of X_i on response probability at the average value of α_i (γ_i= 0). The approach also avoids incidental parameters problem. Assuming possible interdependency on adoption decisions of different technologies.

Intensity of adoption

We define intensity of adoption as the size of the plot in hectares (ha) under DT maize variety and the quantity of DT seed planted. With the possibility of a censored plot size and DT maize seed at plot level, we use correlated random effects Tobit to analyse the intensity of adoption.

Let the size of land that is allocated to a DT maize variety by farmer *i* at time *t* be L_{it}. The unobserved effects Tobit model for a corner at zero for L_{it} can be specified as:

$$L_{it}^* = max(0, \alpha X_{it} + \varepsilon_{it} + \alpha_i) \qquad 5$$

$$D(\varepsilon_{it}|X_{it}, \alpha_i) = N(0, \sigma_\varepsilon^2) \qquad 6$$

where the dependent variable (L_{it}) is the size of the plot in ha (and quantity of DT maize seed planted on the plot) and the explanatory variables are as defined in equation 1(Wooldridge, 2010 pp; 540-542).

Study Areas, Data and Sampling Procedure

The paper uses three-year panel data from six districts in Malawi namely Lilongwe, Kasungu, Chiradzulu, Machinga, Thyolo and Zomba. Agro-ecologically, Chiradzulu, Kasungu, Lilongwe, Machinga, and Zomba districts are located in medium altitude zone which enjoys high average rainfall ranging from 800 – 1,200 mm annually with an altitude of 1,000 to 1,500 metres above sea level although Machinga is partly drought-prone district (Katengeza *et al.*, 2012; Mangisoni *et al.*, 2011). Thyolo district on the other hand belongs to the high plateaux and hilly areas which lie in an altitude over 1,500 above sea level and receives over 1,200 mm of rainfall annually. Agro-ecological and location variables affect adoption of agricultural technologies such as DT maize. Such variables capture variations in rainfall, soil quality, production potential, infrastructure development as well as availability of input and output markets (Doss & Doss, 2006).

The data is based on an original sample of 450 households surveyed in 2006 and 2007 and 376 in 2009, 350 in 2012 and 2015 (Table 1). The initial sample was randomly selected following the 2004 Integrated Household Survey Two (IHS 2). Data collection involves detailed farm plot level information measured with GPS on plot sizes of which a total of 1076, 1387 and 1281 plots are reported in 2009, 2012 and 2015, respectively. The plot is defined in this paper by Holden and Lunduka (2012) as a "*uniform crop stand that received homogenous input treatment*". The quality of the data is better with minimal measurement errors because (1) data is collected from all farm households' plots unlike larger surveys which normally collect data from one plot (2) all plots are measured with GPS as opposed to relying on farmers' estimates which are prone to big errors (Holden & Mangisoni, 2013). This data is also of interest as it captures weather extremes namely, 2009 with good rains, 2012 early drought and 2015 flood and late drought.

Table 1: Study areas

District	**2009**		**2012**		**2015**		**Total**	
	Households	Plots	Households	Plots	Households	Plots	Households	Plots
Thyolo	50	145	47	162	47	168	144	475
Zomba	41	115	76	264	79	272	196	651
Chiradzulu	79	117	37	163	34	120	150	400
Machinga	45	146	47	185	45	161	137	492
Kasungu	90	356	82	388	80	331	252	1,075
Lilongwe	71	197	61	225	65	229	197	651
Total	376	1,076	350	1,387	350	1,281	1,076	3,744

Descriptive Statistics: Dependent and Explanatory Variables

The dependent variables: Drought tolerant maize varieties

Presented in Table 2 are descriptive statistics for the variables. Plot level data was collected on maize varieties planted on the plot. Adoption is measured by whether an individual farm household planted DT maize variety in at least one of the plots while intensity is measured by the area allocated to DT maize. Also included in intensity of adoption is the quantity of DT maize seed planted. We expect an increase in level of adoption over time especially after 2011/12 drought, farmers should adopt more of DT maize as a response to drought shock. The continued implementation of farm input subsidy programme is also expected to further increase adoption. The issue of adoption is however subjective as it may depend on farmers' perceptions. If farmers perceive drought tolerant maize as climate-smart then adoption may increase in response to drought shocks. Contrary, farmers may view DT maize as low yielding compared to other improved maize (OIM) varieties hence adoption may decrease over time. Availability and development of institutions such as agricultural extension services and credit markets also plays important roles in adoption decisions.

Our results show 46% adoption of DT maize in 2009, 54% in 2012 and 59% in 2015. The results are as expected with an upward sloping over the survey years. The question however is whether the increase is due to farmers' response to drought or other factors. Holden and Fisher (2015) reported that the increase in adoption is mainly due to farm input subsidy programme which has over the years disseminated DT maize varieties. The DT maize seed has been an integral component in the FISP package and this has made it easy for farmers to access the seed. In terms of plot area allocated to DT maize there is an increase from 0.224 ha in 2009 to 0.272 ha in 2015. For seed there is also a slight increase from 5.0 kilograms in 2009 to 5.6 kilograms in 2015.

Table 2: Definitions and summary statistics of variables by year

Variables	Description	Year			
		2009	2012	2015	Mean
Dependent variables					
DTmaize	1 if household adopted drought tolerant maize variety	0.456	0.538	0.587	0.531
DTarea	Area in ha under DT maize	0.224	0.257	0.272	0.253
DTseed	Quantity of DT maize seed in Kg	4.969	4.837	5.607	5.139
Independent variables					
Drought variables					
Drought1yrFmr	1 =Farmers perceive drought occurred previous year	0.082	0.273	0.239	0.207
Drought0yrFmr	1 =Farmers perceive drought occurred survey year	0.091	0.441	0.740	0.446
Drought1yr	Times dry spells occurred (actual rainfall) previous year	2.219	1.280	2.736	2.048
Drought0yr	Times dry spells occurred (actual rainfall) survey year	0.757	2.130	3.035	2.045
Earlydrought	Times early dry spells (actual rainfall) previous year	0.000	0.794	0.869	0.591
Latedrought	Times late dry spells (actual rainfall) in survey year	0.000	0.000	0.391	0.134
Institutional variables					
Seedfisp1yr	1=Household received seed subsidy coupon previous year	0.337	0.598	0.696	0.561
Seedfisp0yr	1=Household received seed subsidy coupon survey year	0.370	0.555	0.649	0.538
Extension	1=Household was visited by an extension worker	0.474	0.149	0.290	0.290
Creditinput	1=Household accessed farm input credit	0.105	0.063	0.091	0.085
Plot characteristics					
Logplotdist	Log(plot distance in km + 1)	5.455	5.755	6.278	5.848
Landtenure	1 if operated by plot owner	0.913	0.947	0.931	0.932
Sandy soil	1=Farmers perceive sandy soil	0.244	0.198	0.206	0.214
Loam soil	1=Farmers perceive loam soil	0.479	0.542	0.673	0.569
Clay soil	1=Farmers perceive clay soil	0.273	0.255	0.121	0.214
Flat slope	1=Farmers perceive flat slope on plot	0.582	0.648	0.518	0.584
Moderate slope	1=Farmers perceive moderate slope on plot	0.363	0.297	0.415	0.356
Steep slope	1=Farmers perceive steep slope on plot	0.050	0.048	0.068	0.056
High fertility	1=Farmers perceive high soil fertility on plot	0.178	0.208	0.087	0.158
Medium fertility	1=Farmers perceive medium soil fertility on plot	0.612	0.679	0.705	0.669
Low fertility	1=Farmers perceive low soil fertility on plot	0.204	0.102	0.208	0.167
Plotsize(gps)	Plot size measured by GPS (ha)	0.338	0.296	0.301	0.310
Logplotsize	Log(Plot size in ha)	-1.424	-1.582	-1.592	-1.540
Plotsize(farmer)	Plot size (reported by farmer) (ha)	0.623	0.341	0.366	0.430
Household demographic characteristics					
Age	Age of household head (years)	46.88	51.06	48.94	49.15
Education	Education of household head (years)	4.572	4.983	4.838	4.817
Family size	Total family size (number)	5.554	5.468	5.715	5.578
Sex	1 = If gender of household head is male	0.809	0.763	0.731	0.765
Marital status	1 = If household head is married	0.765	0.731	0.679	0.722
Flabour	Family labour (no of persons)	2.614	2.870	2.623	2.706
Hlabour	Hired labour (no of persons)	0.915	0.817	1.297	1.023

Explanatory variables

The choice of explanatory variables is based on our hypotheses, previous studies and available data. Such variables include (1) rainfall stress variables, (2) plot-level factors (e.g. plot size, perceived soil fertility, slope, soil type, and distance from home. (3) Household level factors (e.g. sex of household head, age, education, family size, family labour, hired labour, and marital status). (5) Institutional factors (e.g. access to extension, input credit, and farm input subsidy programme).

Rainfall stress variables

We define rainfall stress variables in this analysis as those capturing dry spells. Exposure to dry spells is a key variable in the analysis and we assess the extent to which the sampled households were exposed to dry spells in each of the survey years (2009, 2012, and 2015) as well as lagged variables. 74% of the farm households reported drought shock in 2015 while 44% reported drought shock in 2012. This represents severity of drought shock in 2015 and 2012 than in 2009. There is however an element of subjectivity in assessment of dry spell exposure using farm household perceptions (Holden & Quiggin, 2015; Holden & Fisher, 2015). This may result in endogeneity because more pessimistic farmers tend to overestimate the probability of a negative outcome and therefore perceive higher probability of drought shocks. These farmers might also be more risk-averse and more likely to adopt. We therefore constructed an objective drought measure using daily rainfall data from meteorological services department to test whether drought impact adoption of DT maize varieties. In 2015 dry spells occurred at least three times. A dry spell is defined as a period of 10 – 15 days with a total rainfall of less than 20mm following a rainy day of at least 20mm.

Institutional variables

Key institutional variables considered are agricultural extension services, credit access, and access to the Farm Input Subsidy Programme (FISP). Agricultural extension services may remain an important channel for agricultural technologies in Malawi. We measure access to extension services as a dummy variable on whether farm households were visited by an extension officer or not. On average 29% reported being visited by an agricultural extension worker at least once in a growing season. In defining the credit access variable we used the Feder *et al.* (1990) approach which distinguishes between farmers who choose not to participate in credit markets and those who do not have access to credit. Credit-constrained farmers are those who need credit but are unable to get it while credit-unconstrained farmers are those who decide not to participate as well as those who need and are given. Only 35% are credit unconstrained. We, however, note that credit unconstrained may not be enough as farmers may access credit for different reasons, hence we consider only those who accessed credit for farming reasons (e.g. buying inputs). Only 8% accessed input credit. On subsidy, we find that the share of households receiving seed subsidy coupon increased from 37% in 2009 to 65% in 2015. We also included the lagged seed subsidy variable to assess whether previous access to DT maize seed can enhance adoption of the same in the following years.

Plot level variables

Plot-specific variables include, perceived soil fertility, slope, soil type, plot size, fertiliser used on plot, and distance from home. Plot distance from household residence is an important factor that can influence adoption of CSA practices. Longer distances increase transaction costs, for walking and monitoring hence less adoption (Kassie *et al.*, 2015).

Household characteristic variables

Household level factors control for household heterogeneity and these include education of household head, age, sex, marital status, family size, family and hired labour. These variables may influence adoption decisions in countries such as Malawi which have high market imperfections and institutional failures (Kassie *et al.*, 2015). Education increases understanding of shocks such as droughts and floods and the adaptive measures hence increases adoption (Katengeza et al., 2012; Mangisoni et al., 2011). The average educational attainment of household heads is 4.8 years of education in the sampled districts. The average age of the household head is 49 years while about 72% of the sample households are male-headed. In terms of family size, on average, there are five members in each of the sampled households with an active labour force of 2.7. An active labour force is an important variable to explain adoption decisions as some production activities require more labour.

Results and discussion

DT maize adoption

Table 3 are results of determinants of adoption of drought tolerant maize varieties. Our primary objective is to examine whether exposure to drought enhances adoption of DT maize. Farmers in Malawi were exposed to early droughts in 2012 and late droughts in 2015 in addition to dry spells in other years. The first Probit model (probit 1) uses two drought variables, namely, farmer perception dummy variable given a value of one if a farmer perceives drought occurred in a given year and a variable capturing number of times dry spells occurred in each of the three years and their lagged variables. Although the coefficients of the probit model were not different from the marginal effects, presented here are marginal effects. The results show a positive and significant relationship between farmers' exposure to drought and adoption of drought tolerant maize varieties. Both the subjective (farmers' perception) and objective drought variables increase the probability of adopting DT maize. This result is consistent with our expectation and the findings of Holden and Fisher (2015) that farmers who previously were exposed to drought are more likely to adopt DT maize as an adaptive mechanism. Ding *et al.* (2009) also reported that farmers' experience with drought increases their likelihood of adopting conservation tillage systems.

However lagged drought variables for both farmer perception and rainfall data are associated with negative impact on adoption. The possible explanation is that the years preceding survey years were normal years with no serious reported droughts. Therefore the drought tolerant maize varieties would not have been necessary as farmers expected a normal year as previous.

The second probit (probit 2) expand the first model by replacing the aggregate drought variable with early and late dry spells. We define early drought as a period between December and early January which is planting time while late drought is a period between February and early March which is a period of maize flowering and grain formation. The early drought appears to have a greater impact on DT maize adoption than late drought. Farmers who are exposed to early and late drought are 31% and 20% more likely to adopt DT maize, respectively. The possible explanation is that early drought acts as early warning to farmers such that farmers are more likely to buy and plant maize varieties which are drought tolerant. Another explanation is that early drought affects germination of maize forcing farmers to replant. Replanting implies farmers buying more of early maturing varieties to fit into the growing season as Malawi has a unimodal type of rainy season which ends by late March or early April. Although other hybrids are also early maturing, the 2012 experience shows that most farmers opt for DT early maturing maize varieties (Holden & Fisher, 2015) e.g. SC403 (Kanyani). The impact of drought on adoption of DT maize is also supported by the district dummy variables. Farmers in Machinga a drought prone district (Katengeza *et al.*, 2012) are 35% more likely to adopt drought tolerant maize and likely to increase plot size planted with DT maize seed by 58% than farmers in Thyolo who receive more and stable rainfall.

Tobit models are for intensity of adoption using land sizes (in hectares) allocated to drought tolerant maize and quantity of DT maize seed planted. In Tobit 1 we use the farmer perception variable of drought as well as early and late drought variables on land under DT maize. Tobit 2 and Tobit 3 uses the control function approach on proportion of land and quantity of seed, respectively. The results are consistent with the probit results where exposure to drought is associated with likelihood of increasing acreage of land under DT maize as well as increasing quantity of seed planted. Early droughts are more likely to increase acreage of land allocated to drought tolerant maize by 33% and the quantity of drought tolerant maize seed bought by 86%.

The paper also tests the impact of access to farm input subsidy programme on adoption of DT maize varieties. Access to FISP increases adoption by 34-37%. The results are in agreement with Holden and Fisher (2015) who reported FISP as a strongest driver of adoption of DT maize. However while access to seed subsidy input increases both adoption and intensity of adoption, previous year's access has a negative impact on adoption. This suggests that the increased adoption is due to the availability of cheap seed as opposed to farmers' previous exposure with the drought tolerant maize varieties. A plausible explanation is the lack of information on the benefits of the DT maize varieties. Fisher *et al.* (2015) reported that about 40% of small holder farmer did not grow DT maize varieties because of poor labelling of DT maize packages. There is yet to be a very clear labelling of DT maize varieties that provide enough information to farmers to make informed decision. This has been achieved in early maturing varieties like SC403 by SEEDCO that have used a symbol of a monkey to show speed and fast maturity of the early maize variety.

Visits by agricultural extension workers, flat slope, high soil fertility, are also associated with high adoption while distance to plot and plot sizes reduces the likelihood of adoption. The positive significance of extension visits confirms the importance of increased awareness of the varieties to enhance adoption. Controlling for household heterogeneity, the results show that education, age and being married are associated with less probability of adoption while household size and family labour increases the likelihood of both adoption and adoption intensity. Hired labour is also associated with the increased probability of allocating more land to DT maize cultivation as well as increasing DT maize seed.

Table 3: Correlated Random Effects Probit (marginal effects) and Tobit Models with Control Function Approach

Variables	Probit 1 (b/se)	Probit 2 (b/se)	Tobit (Plot size) (b/se)	Tobit with CFA (b/se)	Tobit with CFA (Quantity dt seed) (b/se)
Drought variables					
Drought1yr (Times of dry spell occurrence previous year)	-0.044*				
	-0.020				
Drought0yr (Times of dry spell occurrence survey year)	0.065***				
	-0.020				
Drought1yrFmr (1 if farmer perceives drought occurred previous year)	-0.070	-0.170***	-0.103***	-0.246***	-0.440***
	-0.060	-0.060	-0.030	-0.030	-0.060
Drought0yrFmr (1 if farmer perceives drought occurred survey year)	0.353***	0.211***	0.158***	0.385***	1.009***
	-0.050	-0.050	-0.030	-0.030	-0.050
Early drought (Dec to early Jan)		0.309***	0.102***	0.329***	0.863***
		-0.060	-0.030	-0.030	-0.060
Late drought (Feb to early March)		0.199**	0.100**	0.313***	0.823***
		-0.090	-0.050	-0.040	-0.080
Institutional variables					
Access to seed subsidy previous year	-0.101*	-0.101*	-0.058*	-0.145***	-0.471***
	-0.060	-0.060	-0.030	-0.030	-0.060
Access to seed subsidy in survey year	0.375***	0.341***	0.130***	0.399***	1.099***
	-0.060	-0.060	-0.030	-0.030	-0.060
Extension visits	0.159***	0.187***	0.116***		
	-0.050	-0.050	-0.030		
Input credit	-0.029	0.003	-0.088*	-0.159***	-0.139*
	-0.080	-0.080	-0.050	-0.040	-0.080
Plot characteristics					
Moderate slope	-0.226***	-0.170***	-0.123***	-0.242***	-0.502***
	-0.050	-0.050	-0.030	-0.020	-0.050
Steep slope	-0.403***	-0.240**	-0.197***	-0.407***	-0.999***
	-0.100	-0.110	-0.060	-0.050	-0.110
Medium fertility	-0.154**	-0.149**	-0.017	-0.160***	-0.492***
	-0.070	-0.070	-0.040	-0.030	-0.060
Low fertility	-0.087	-0.096	-0.054	-0.130***	-0.331***
	-0.090	-0.090	-0.050	-0.040	-0.080
Loam soil	-0.015	0.049	0.048	0.119***	0.391***
	-0.060	-0.060	-0.030	-0.030	-0.060
Clay soil	-0.048	0.018	0.099**	0.148***	0.105
	-0.070	-0.070	-0.040	-0.030	-0.070

Log plot distance	-0.050***	-0.051***	-0.019**	-0.074***	-0.210***
	-0.010	-0.010	-0.010	-0.010	-0.010
Log plot size	0.002	-0.003	0.064***	0.091***	0.061**
	-0.030	-0.030	-0.010	-0.010	-0.030
Household characteristics					
Education	-0.020***	-0.019***	-0.004		
	-0.010	-0.010	0.000		
Sex of household head (1=male)	0.507***	0.483***	0.216***		
	-0.100	-0.100	-0.050		
Household size	0.041***	0.045***	0.036***		
	-0.010	-0.010	-0.010		
Age	-0.012*	-0.011	-0.004		
	-0.010	-0.010	0.000		
Age squared	0.000**	0.000*	0.000		
	0.000	0.000	0.000		
Marital status (1=married)	-0.480***	-0.464***	-0.232***	0.000	
	-0.090	-0.090	-0.050	0.000	
Family labour	0.038**	0.048***	0.032***	0.075***	0.171***
	-0.020	-0.020	-0.010	-0.010	-0.020
Hired labor	0.024**	0.020**	0.009*	0.027***	0.075***
	-0.010	-0.010	-0.010	0.000	-0.010
Location variables (district dummies)					
Zomba		-0.021	0.034	0.026	0.274**
		-0.120	-0.070	-0.060	-0.120
Chiradzulu		0.127	0.024	0.210***	0.681***
		-0.100	-0.060	-0.050	-0.100
Machinga		0.354***	0.165***	0.581***	1.887***
		-0.110	-0.060	-0.050	-0.110
Kasungu		0.051	0.159***	0.301***	0.770***
		-0.090	-0.050	-0.040	-0.090
Lilongwe		-0.103	-0.006	-0.081	-0.238*
		-0.120	-0.070	-0.060	-0.120
Error from adoption equation				1.287***	3.437***
				-0.030	-0.070
Constant	0.330	0.171	-0.147	-0.808***	-1.436***
	-0.240	-0.250	-0.140	-0.100	-0.200
Prob > chi2	0.000	0.000	0.000	0.000	0.000
Number of household (plot) observations	3300	3300	3300	3300	3300

Conclusions and implications

Weather extremes especially recurrent droughts threaten agricultural productivity and food security in Malawi whose population largely depend on maize for food. Drought tolerant maize is one promising technology to minimise the grinding impact of drought. In recent times several drought tolerant maize varieties have been developed by national research institutions in collaboration with CIMMYT researchers and have been disseminated across the country. Examining determinants of adoption of this promising technology is increasingly becoming important. Following the work of Holden and Fisher (2015) and Fisher *et al.* (2015) this paper has used correlated random effects probit and tobit models with control function approach to understand adoption of DT maize in Malawi under rainfall stress. The data is from farm households in six districts collected in 2009, 2012 and 2015 using a sample size of 376 in 2009 and 350 for 2012 and 2015. The year 2009 is used as control since no serious drought shock was reported.

Holden and Fisher (2015) reported a substantial increase in adoption of DT maize from 2006 to 2012, and this study also finds a significant increase from 46% in 2009 to 59% in. The paper has found strong evidence of the impact of drought on increased adoption. This implies that farmers learn from exposure to drought and respond by adopting risk reducing technologies such as DT maize varieties. Farmers in drought prone districts such as Machinga are more likely to adopt DT maize varieties than their counterparts in districts with high and stable rainfall such as Thyolo. Lagged variables of drought are however associated with less likelihood of adoption. This could be due to the fact that the years preceding the surveys were associated with normal rains such that farmers responded by adopting less of DT maize in anticipating of similar good rains. Farmers may thus respond by adopting more of improved hybrids as opposed to DT maize.

Another important driver of adoption also reported by Holden and Fisher (2015) is the farm input subsidy programme. However while access to seed subsidy input increases both adoption and intensity of adoption, the lagged variable of access to seed subsidy has a negative impact on adoption. This suggests that the increased adoption is due to the availability of cheap seed as opposed to farmers' previous exposure with the drought tolerant maize variety. This may indicate limited awareness on the benefits of drought tolerant maize varieties. This is also consistent with extension visits positively affecting adoption.

The understanding that farmers respond to exposure to weather shocks is an important observation to maize seed breeders, agricultural extension workers and other development partners to further promote the climate risk reducing technologies. Promotion of technologies which are perceived by farmers themselves as climate-smart based on their experience are more likely to receive high adoption rates and make an impact to the general livelihood. In Malawi with FISP contributing significantly to the adoption, extension messages should be intensified with empirical evidence so that farmers can continue using the DT seed even after FISP. It is imperative however to understand that farmers in Malawi respond more to early droughts which acts as early warning by adopting more of early maturing varieties. Breeders should thus respond by breeding and disseminating more early maturing DT maize as opposed to late maturing DT maize seed. More importantly good extension messages and promotion of drought tolerant maize varieties should be improved to allow farmers make informed decisions.

References

Arslan, A., McCarthy, N., Lipper, L., Asfaw, S., & Cattaneo, A. (2014). Adoption and intensity of adoption of conservation farming practices in Zambia. *Agriculture, Ecosystems & Environment, 187*, 72-86. doi: 10.1016/j.agee.2013.08.017

Asfaw, S., McCarthy, N., Lipper, L., Arslan, A., Cattaneo, A., & Kachulu, M. (2014). Climate variability, adaptation strategies and food security in Malawi. *ESA Working Paper No. 14-08. Rome, FAO.*

Chamberlain, G. (1980). Analysis of Covariance with Qualitative Data. *The Review of Economic Studies*, 225-238.

Davies, M., Guenther, B., Leavy, J., Mitchell, T., & Tanner, T. (2009). Climate change adaptation, disaster risk reduction and social protection: complementary roles in agriculture and rural growth? *IDS Working Papers, 2009*(320), 01-37.

Devereux, S. (2007). The impact of droughts and floods on food security and policy options to alleviate negative effects. *Agricultural Economics, 37*(s1), 47-58.

Ding, Y., Schoengold, K., & Tadesse, T. (2009). The Impact of Weather Extremes on Agricultural Production Methods: Does drought increase adoption of conservation tillage practices? *Journal of Agricultural and Resource Economics*, 395-411.

Doss, C. R., & Doss, C. (2006). Analyzing Technology Adoption, Challenges and limitations of micro studies. *Agricultural economics, 34*, 207-219.

Feder, G., Lau, L. J., Lin, J. Y., & Luo, X. (1990). The relationship between credit and productivity in Chinese agriculture: A microeconomic model of disequilibrium. *American Journal of Agricultural Economics*, 1151-1157.

Fisher, M., Abate, T., Lunduka, R. W., Asnake, W., Alemayehu, Y., & Madulu, R. B. (2015). Drought tolerant maize for farmer adaptation to drought in sub-Saharan Africa: Determinants of adoption in eastern and southern Africa. *Climatic Change, 133*(2), 283-299.

Garrity, D. P., Akinnifesi, F. K., Ajayi, O. C., Weldesemayat, S. G., Mowo, J. G., Kalinganire, A., . . . Bayala, J. (2010). Evergreen Agriculture: a robust approach to sustainable food security in Africa. *Food security, 2*(3), 197-214.

Holden, S., & Fischer, M. (2015). Can Adoption of Improved Maize Varieties Help Smallholder Farmers Adapt to Drought? Evidence from Malawi: Centre for Land Tenure Studies, Norwegian University of Life Sciences.

Holden, S., & Lunduka, R. (2012). Do fertilizer subsidies crowd out organic manures? The case of Malawi. *Agricultural Economics, 43*(3), 303-314.

Holden, S., & Mangisoni, J. (2013). Input subsidies and improved maize varieties in Malawi: What can we learn from the impacts in a drought year? : Centre for Land Tenure Studies, Norwegian University of Life Sciences.

Holden, S., & Quiggin, J. (2015). Climate risk and state-contingent technology adoption: The role of risk preferences and probability weighting.

Holden, S. T., & Fisher, M. (2015). Subsidies promote use of drought tolerant maize varieties despite variable yield performance under smallholder environments in Malawi. *Food Security, 7*(6), 1225-1238.

Kassie, M., Teklewold, H., Jaleta, M., Marenya, P., & Erenstein, O. (2015). Understanding the adoption of a portfolio of sustainable intensification practices in eastern and southern Africa. *Land Use Policy, 42*, 400-411.

Kassie, M., Teklewold, H., Marenya, P., Jaleta, M., & Erenstein, O. (2014). Production Risks and Food Security under Alternative Technology Choices in Malawi: Application of a Multinomial Endogenous Switching Regression. *Journal of Agricultural Economics*.

Kassie, M., Yesuf, M., & Köhlin, G. (2009). The role of production risk in sustainable land-management technology adoption in the Ethiopian Highlands. *rapport nr.: Working Papers in Economics 407*.

Katengeza, S. P., Mangisoni, J. H., Kassie, G. T., Sutcliffe, C., Langyintuo, A., La Rovere, R., & Mwangi, W. (2012). Drivers of improved maize variety adoption in drought prone areas of Malawi. *Journal of Development and Agricultural Economics 4*(14), 393-403.

Kato, E., Ringler, C., Yesuf, M., & Bryan, E. (2011). Soil and water conservation technologies: a buffer against production risk in the face of climate change? Insights from the Nile basin in Ethiopia. *Agricultural Economics, 42*(5), 593-604.

Lipper, L., Thornton, P., Campbell, B. M., Baedeker, T., Braimoh, A., Bwalya, M., . . . Henry, K. (2014). Climate-smart agriculture for food security. *Nature Climate Change, 4*(12), 1068-1072.

Magorokosho, C., Vivek, B., & MacRobert, J. (2009). Characterization of maize germplasm grown in eastern and southern Africa: Results of the 2008 regional trials coordinated by CIMMYT.

Mangisoni, J. H., Katengeza, S., Langyintuo, A., Rovere, R., & Mwangi, W. (2011). Characterization of maize producing households in Balaka and Mangochi Districts in Malawi. *Country Report–Malawi. Nairobi: CIMMYT*.

Nangoma, E. (2007). National adaptation strategy to climate change impacts: A case study of Malawi. *Human Development. UNDP. Report, 2008*.

Pangapanga, P. I., Jumbe, C. B., Kanyanda, S., & Thangalimodzi, L. (2012). Unravelling strategic choices towards droughts and floods' adaptation in Southern Malawi. *International Journal of Disaster Risk Reduction, 2*, 57-66.

Pauw, K., Thurlow, J., Bachu, M., & Van Seventer, D. E. (2011). The economic costs of extreme weather events: a hydrometeorological CGE analysis for Malawi. *Environment and Development Economics, 16*(02), 177-198.

Pauw, K., Thurlow, J., & van Seventer, D. (2010). *Droughts and floods in Malawi: assessing the economywide effects*: International Food Policy Research Institute (IFPRI).

Wooldridge, J. M. (2009). *New Developments in Econometrics, Lecture 6: Non-linear Panel Data Models. Cemmap Lectures.* University College London. Retrieved from http://www.cemmap.ac.uk/resources/imbens wooldridge/slides 6.pdf

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*: MIT press.

Wooldridge, J. M. (2014). *Introduction to Econometrics* (Europe, Middle East & Africa ed.): Cengage Learning EMEA, Hampshire, UK